Real-time Bayesian Data Assimilation and Prediction for Livestock Epidemics

Chris Jewell[1], Will Probert[2], Mike Tildesley[2]

[1]CHICAS, Lancaster University, c.jewell@lancaster.ac.uk
[2]Life Sciences, University of Warwick

27th October, 2016

Aims

During an epidemic, we wish to use a model for...

- Nowcasting:
  - What is the current extent of the epidemic?
  - What puts a farm at high risk?
  - Is our current control strategy working?

- Forecasting:
  - Where will the disease go next?
  - What is the best control decision, given imperfect knowledge?

CHICAS centre for health informatics, computing, and statistics

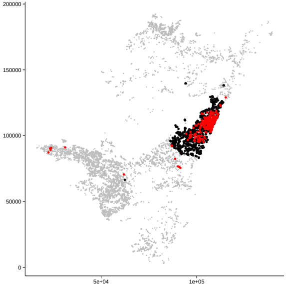
Japanese foot and mouth disease, 2010

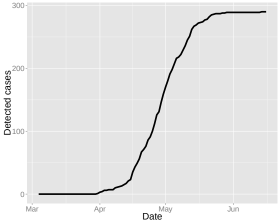
Muroga *et al.* (2012)

- Miyazaki prefecture
- First detection late March 2010
- Day 0 = date of first detection

- 290 IPs
- 948 non-IP culls

- 10km vaccination implemented days 60–64
- DC culls mostly > day 84





Nowcasting questions

At each stage of the epidemic:

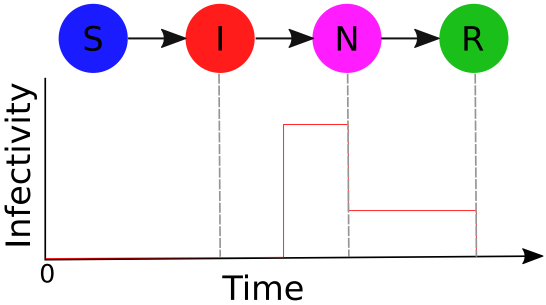
- Evaluate control policy
  - Vaccine efficacy
- What was the true extent of the outbreak?
  - Where are the undetected, or occult infections?
  - Vaccination strategy
  - Cull strategy
  - Target surveillance

Available data

I think like a statistician: data $\Longrightarrow$ model!

- Population data (explanatory variables):
  - Location of each farm: centroid, UTM coordinates
  - Number of cattle, pigs
  - Date of vaccination (∞ if not vaccinated)
- Epidemiological data (response variable(s)):
  - Detection (notification) date
  - Cull date
- Infection date not observed $\Longrightarrow$ censored

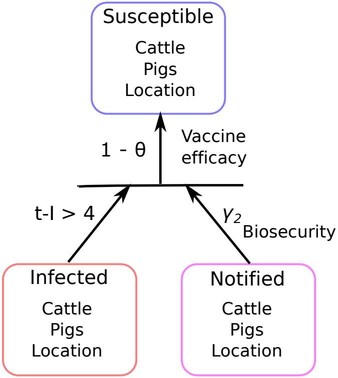
SINR model



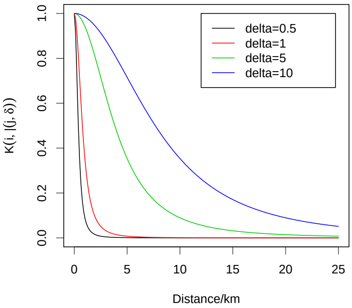
- Farm as epidemiological unit
- Infections determined by relationship to other infectives
- Infection times are censored (unobserved)
  - Undetected occult infections

Transmission model – quickly!

Keeling *et al.* 2001



Spatial SINR Model

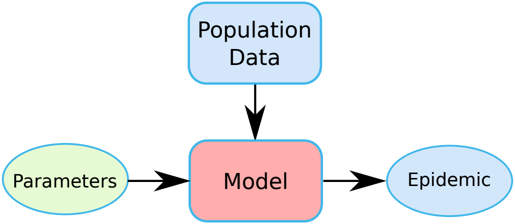


Spatial transmission (proxy for network)

CHICAS centre for health informatics, computing, and statistics

Model-based inference

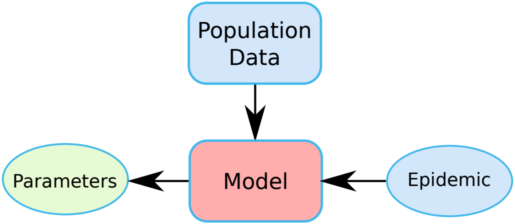
- Simulation moves forward in time
- Parameters unknown



- Prior to simulation, we need parameter inference

Inference

- Parameter inference looks backward in time
- Done in real-time during epidemic
- Inference requirements
  - Parameters estimated with full measurement of uncertainty
  - Account for censored and occult infection times
  - Easy to feed forward into simulation



Bayesian Inference

1. Incorporation of prior information
2. Machinery to account for missing data
    - Censored infection times
    - occult (undetected) infections
3. Fully likelihood-based
    - We know what we're getting from our model! (cf. ABC)
    - Likelihood fast to compute (cf. simulation)
    - GPU accelerated MCMC $\rightarrow$ results overnight!
4. Results provided as (posterior) probability distributions
    - Suitable for decision making under uncertainty
    - Don't be over-confident!

Vaccine efficacy

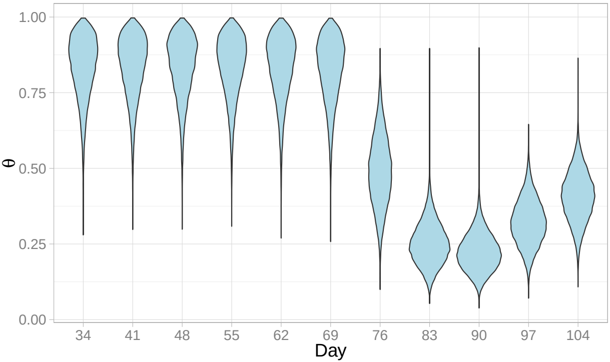
How effective was vaccination?

- Vaccine efficacy: θ parameter

$$s(j; t, \zeta, \phi) = (1-\theta)^{[v_j<t]} \left(\tilde{c}_j^{\,\phi_c} + \zeta \tilde{p}_j^{\,\phi_p} \right)$$

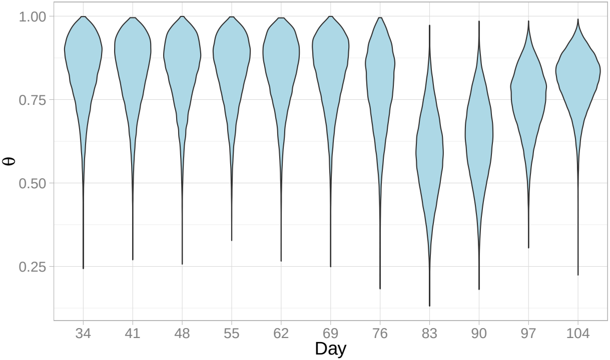
- Vaccine efficacy tested 4, 8, 16 days post vaccination
- Results from weekly analyses during outbreak
- N.B. results from epidemic model avoids bias due to non-independence of infections

Vaccine efficacy
4 days post-vaccination



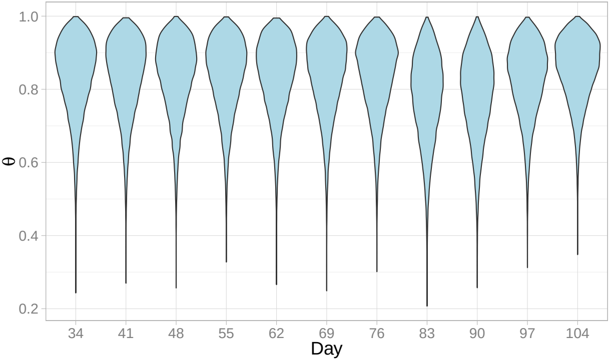
Efficacy 4 days post vaccination

Vaccine efficacy
8 days post-vaccination



Efficacy 8 days post vaccination

Vaccine efficacy
14 days post-vaccination



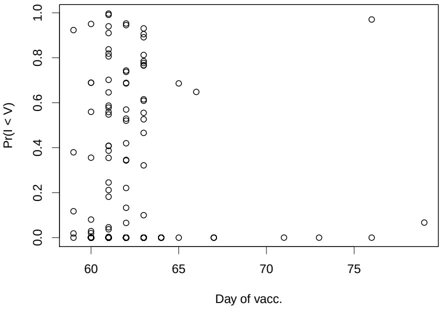
Efficacy 14 days post vaccination

Vaccination timing

- Was vaccination performed in time?

Vaccination timing

- Was vaccination performed in time?
- What was the probability that herds were already infected when they were vaccinated? (Preliminary results!)



Extent of the epidemic

- Was vaccination and/or DC culling keeping up with the epidemic?
- Nowcasting of undetected infections can tell us...

Show movie now...

Conclusions
Methods

- Likelihood-based inference is fast: nowcast information $\approx$ 1h
    - Suitable for epidemic management *if* data comes in promptly!
    - Work on automated data pipeline to improve this
- Joint parameter posterior provides basis for forecasting
    - See Will Probert's talk up next...
- GPU-enabled code available at `http://fhm-chicas-code.lancs.ac.uk/groups/InFER/`
    - Help provided to compile and/or develop the model!

CHICAS centre for health informatics, computing, and statistics

Conclusions
Japan 2010

- Apparent vaccine efficacy highly sensitive to delay between dose and immunity
  - Vaccine takes time to work – need to be ahead of the epidemic!
  - Eventual efficacy around 85%, but epidemic escapes vaccine delivery.
- Knowledge of spatial extent of the epidemic required
  - Optimise vaccine delivery, culling
  - Occult probabilties: prioritise active surveillance (see Jewell *et al* (2012) *Biostatistics*)
- More precise results: we need to to negative testing results as well as positive

The end

Transmission model – less quickly!

Susceptible $\rightarrow$ Infected

$$\lambda_{ij}(t) = \gamma_1 q\left(i; \boldsymbol{\xi}, \boldsymbol{\psi}\right) s\left(j; \boldsymbol{\zeta}, \boldsymbol{\phi}\right) K(i, j; \delta) \qquad i \in \mathcal{I}, j \in \mathcal{S}$$

$$\lambda^*_{ij}(t) = \gamma_2 \beta_{ij}(t) \qquad i \in \mathcal{N}, j \in \mathcal{S}$$

$$\epsilon_t = \begin{cases} \epsilon_1 & \text{if } t < \mu \\ \epsilon_1 \epsilon_2 & \text{otherwise} \end{cases}$$

$$q(i; t, \boldsymbol{\xi}, \boldsymbol{\psi}) = \mathbf{1}[t - Ii > 4] \left(\tilde{c}_i^{\psi_1} + \xi \tilde{p}_i^{\psi_p} \right)$$

$$s(j; t, \boldsymbol{\zeta}, \boldsymbol{\phi}) = (1 - \theta)^{[v_j < t]} \left(\tilde{c}_j^{\phi_c} + \zeta \tilde{p}_j^{\phi_p} \right)$$

$\tilde{c}, \tilde{p}$ = cattle, pigs; ϵ_2 = movt ban; γ_2 = notification

v = vaccine effect date; θ = farm-level vaccine efficacy